Stuck in the Prompt Loop? Rumination and GenAI Use

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ABSTRACT,

Generative artificial intelligence is rapidly attracting users worldwide and is integrated into their everyday lives. While digital technology use has been linked to negative mental outcomes, including rumination, the relationship between rumination and GenAI use is underexplored, because of its novelty.

A quantitative survey was conducted with 164 participants, assessing GenAI use intensity, productive and non-productive patterns of use, rumination, personality traits, and demographics, including age, gender, and occupation.

This study concludes that rumination is associated with the patterns of GenAI use, not its duration. The research contributes to human-AI interaction literature by deepening the understanding of GenAI use and the importance of individual differences.

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Keywords
Human-AI interaction, Rumination, Generative Artificial Intelligence, GenAI Use Intensity, GenAI Use Patterns, Personality Traits

During the preparation of this work, the author used ChatGPT in order to improve clarity and grammar of the text and to debug code errors in RStudio. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

1. INTRODUCTION

Artificial intelligence (AI) is a substantial component of the Fourth Industrial Revolution, influencing how people live, work, communicate, and think (Feuerriegel et al., 2023; Hildebrand, 2019; Loerakker et al., 2024; Ross & Maynard, 2021). It brings significant changes into the world (Agbaji et al., 2023).

Generative artificial intelligence (GenAI) tools are rapidly attracting users worldwide, as shown by ChatGPT gaining 1 million users in the first 5 days (Buchholz, 2023). The McKinsey survey conducted in 2024 with 1363 participants reported that respondents used GenAI tools regularly. 13% used them for work, 16% outside of work, and 26% used them for both, showing an increase in adoption from a survey conducted 1 year earlier (Singla et al., 2024).

Generative artificial intelligence (GenAI) refers to machine learning solutions that can produce seemingly novel and meaningful content based on training data and user input (Cress & Kimmerle, 2023; Sætra, 2023). GenAI's output is highly dependent on these input prompts (Cress & Kimmerle, 2023; Federiakin et al., 2024). To achieve the optimal result, users need to apply various cognitive skills and abilities, for example, problem-solving (Federiakin et al., 2024; Lazovsky et al., 2024).

Notably, these skills are not only important in using GenAI tools but also can be affected by it both positively through active engagement (Zhou et al., 2024) and negatively through overreliance (Gerlich, 2025). While active engagement with GenAI might foster cognitive capabilities (Moongela et al., 2024), overreliance raises concerns about cognitive off-loading and reduced critical thinking, both associated with more intense GenAI use (Gerlich, 2025).

More intense use of digital technology and digital addiction are commonly observed among people with ruminative tendencies (Gao & Du, 2025; Hu et al., 2023). Rumination hinders attention, concentration, motivation, and the aforementioned problem-solving while introducing negatively biased thinking (Loerakker et al., 2024; Nolen-Hoeksema et al., 2008). Recent work also draws attention to the risks of various technologies triggering rumination (Loerakker et al., 2024).

While the definition of rumination varies, in literature it is commonly characterized by self-focused, negative, repetitive, passive, and often uncontrollable thinking patterns, where one is "stuck" in focusing on negative feelings, concerns, or experiences and their meaning or consequences without changing the situation (Eikey et al., 2021; Nolen-Hoeksema et al., 2008; Russell, 2021; Watkins, 2008). It is not only a trait someone might have but also a state one might be in, which can change over time or in different contexts (Eikey et al., 2021). It is common among individuals with and without clinical disorders (Joubert et al., 2022). Recent survey-based research shows the prevalence of rumination in the general public. It shows that in the sample of 106 community and 101 undergraduate student participants, 38.4% of respondents reported ruminating and/or worrying daily, and 26% reported doing it more than half of the days a week (Joubert et al., 2022). Rumination is not only common (Ciarocco et al., 2010), but it is also extensively documented as being associated with anxiety disorders and major depressive disorder (Ehring, 2021).

It is worth noting that a recent randomized controlled trial study done by researchers at Dartmouth College showed that by using GenAI tool "Therabot", participants experienced a notable reduction in symptoms of major depressive disorder, generalized anxiety disorder and symptoms of those, who have high risk for developing feeding and eating disorders (Heinz et al., 2025). The exploration of GenAI tools in mental health has been increasing to potentially help areas with health professional shortages. Globally the mental health burden has increased quicker than the growth of mental health professionals (L. Wang et al., 2025; Tal et al., 2023).

Overall, GenAI brings accessible utility for both cognitive task off-loading (Gerlich, 2025) and emotional support (Chan, 2025; Y. Wang et al., 2025). However, it is essential to acknowledge its shortcomings and risks, especially considering the cognitively or psychologically vulnerable population.

1.1 Problem Statement and Research Gap

The current literature recognises that AI can bring new opportunities and improvements, as well as harm (Chan, 2025; Chandra et al., 2024; Du, 2025; M. Huang et al., 2024; Tal et al., 2023). While individuals can turn to it for emotional support (Chan, 2025; Y. Wang et al., 2025), its impact on user's psychological well-being is becoming an increasing concern (OpenAI & MIT Media Lab, 2025). In order to understand such different claims, contextual research on interactions between users and genAI tools are needed (Hipgrave et al., 2025).

Furtherly, existing research has established links between use of technology and various negative mental health outcomes (Shannon et al., 2022), including rumination (Gao & Du, 2025; Hu et al., 2023; Loerakker et al., 2024).

However, genAI is a novel technology that exhibits unique capabilities, such as generating human-like conversations (Cress & Kimmerle, 2023), creating content (Feuerriegel et al., 2023) and simulating social support (Chan, 2025; OpenAI & MIT Media Lab, 2025). Thus, the research on older digital tools cannot be simply transferred to this relationship, and require further investigation.

Lastly, the current research on mental health and genAI has been largely focused on the use of genAI tools for emotional support. However research on how individuals use these tools ordinarily is needed (De Freitas & Cohen, 2024).

1.2 Research Objective and question

The aim of this study is to investigate whether and to what extent the intensity and purpose of GenAI use are associated with different degrees of rumination. Subsequently, two research questions are established:

RQ1 Is the GenAI use intensity associated with the level of rumination?

RQ2 Do GenAI usage patterns moderate the relationship between GenAI use intensity and rumination levels?

2. LITERATURE REVIEW

2.1 Rumination

2.1.1 Dimensions of Rumination

Research suggests that there are two main components of rumination: brooding and reflection. Brooding is the passive comparison of one's current state against unachieved standards or goals (Treynor, 2003). With questions like "Why do I always react this way?" or "What am I doing to deserve this?" (Treynor, 2003), it reflects getting stuck in negative thought without moving forward (Heissel et al., 2023).

Reflection or Reflective Pondering involves attempting to understand the reason for one's feelings or situation within the context of responding to a negative mood (Treynor et al., 2003). It may involve analyzing events or writing down thoughts to analyze (Watkins, 2008). Brooding is maladaptive, whereas reflection may be adaptive (Walbridge, 2021), however it can still be associated with negative outcomes (Miranda & Nolen-Hoeksema, 2007).

2.1.2 Initiators and Triggers

Understanding the factors that trigger rumination establishes a basis to hypothesize how GenAI use might interact with this process. The following triggers are found: experience of stress and goal discrepancies (Michl et al., 2013; Watkins & Roberts, 2020), one's personality traits (Abdollahi, 2019; Slavish et al., 2017), automatic response (Ehring, 2021; Watkins, 2008; Watkins & Roberts, 2020), cognitive factors (Watkins & Roberts, 2020), biological predispositions and environmental factors (Kim et al., 2017).

The experience of stress might increase engagement in rumination, especially in case of uncontrollable and chronic stressors (Michl et al., 2013). Moreover, the link between stress and rumination is bidirectional, where stress triggers rumination, which in turn might prolong the stress response and increase reactivity to another upsetting event (Ruscio et al., 2015).

Goal discrepancies refer to a gap between one's desired and current state. Rumination might occur, when the discrepancy cannot be easily resolved (Michl et al., 2013), aligning with Goal Progress Theory, where rumination is viewed as thinking about unattained goals (Smith & Alloy, 2008).

Furtherly, rumination is linked to some personality traits such as perfectionism (Abdollahi, 2019) and neuroticism (Slavish et al., 2017). While neuroticism refers to a general "tendency to perceive one's environment as threatening and difficult to manage" (Slavish et al., 2017), perfectionism, when individuals strive for an excessively high standard and evaluate themselves critically (Hewitt & Flett, 2002), amplifies the perceived discrepancy from their goal. It results in negative thoughts and lower self-confidence that also correlates with ruminations (Abdollahi, 2019).

One might dwell on problems consciously, however if done often, it might turn into a mental habit (Watkins & Roberts, 2020) where rumination might be triggered without an individual's intent to do so (Ehring, 2021; Watkins 2008).

Furthermore, rumination is triggered by cognitive factors and metacognitive beliefs, such as negative information-processing bias, believed usefulness of rumination and its uncontrollability (Watkins & Roberts, 2020).

Finally, biological predispositions and environmental factors also increase vulnerability to developing ruminative tendencies (Kim et al., 2017).

2.2 The Use of Generative AI

By learning from a large amount of data, GenAI can create various types of seemingly new content, including text, images and videos, sound, speech, music and code based on the user's input. This variety, ease of use and accessibility has increased GenAI's level of maturity, making it useful for many (Feuerriegel et al., 2023; Sætra, 2023).

2.2.1 Generative AI use for Productive Tasks

Productive tasks are characterised as output-oriented (Autor, 2013), desirably effective and efficient (De Been et al., 2016), usually within work or academic contexts. In these interactions, GenAI provides the advantages of productivity through automation and augmentation. Users can delegate tasks to be fully done by GenAI, or they can collaborate with it to enhance their own capabilities (M. Huang et al., 2024).

Within productive use, Anthropic (2025), developer of Claude, identified different interaction patterns among students such as Direct Problem Solving (seeking specific answers) and Direct Output Creation (requesting finished content), as well as more interactive modes like Collaborative Problem Solving and Collaborative Output Creation where users engage in discussion with AI.

GenAI use is being actively used by people across various occupations, including computer and mathematical, arts and media, education and library, office and administrative, business and financial, life, physical and social sciences (Handa et al., 2025).

2.2.2 Generative AI use for Non-Productive Tasks

Beyond task execution and productivity, GenAI tools can also be used for non-productive purposes. It may include entertainment, such as generating creative stories, poems, or images for personal enjoyment. Users may interact with the tool out of curiosity, exploring its capabilities, using it for casual learning without a specific goal. In other cases, users may interact with it to pass the time.

Additionally, conversational AI (CAI) like chatbots are used for social simulation and virtual companionship, offering interaction and feeling of connection (Morales-García et al., 2024; Skjuve et al., 2024). Some individuals turn to AI for emotional exploration, venting feelings, or seeking basic emotional support, leveraging the perceived non-judgmental space (Chan, 2025; Y. Wang et al., 2025).

2.3 Generative AI use and Mental Health

The relationship between GenAI use and mental health can be both positive and negative (Chandra et al., 2024).

On one hand, GenAI tools are explored as accessible means for mental health support, offering psychoeducation, companionship, or even simple therapeutic techniques. Their 24/7 availability and perceived anonymity may reduce barriers to seeking help (Khawaja & Bélisle-Pipon, 2023).

On the other hand, concerns exist regarding negative consequences that the use of GenAI may cause. Over reliance on GenAI could lead to dependency or addiction-like behaviours (Du, 2025). Interaction with AI might trigger or exacerbate anxiety, including "AI Anxiety" that is related to fear of job displacement or loss of control (Frenkenberg & Hochman, 2025; Pinto et al., 2023). Excessive cognitive offloading onto AI might diminish critical thinking skills (Lee et al., 2025). Furthermore, exposure to biased, inaccurate, or harmful AI-generated content could cause emotional distress (X. Huang et al., 2025).

The impact likely depends on characteristics of individual users and the nature of their interactions with the technology (S. Huang et al., 2024).

2.4 Conceptual Framework and Hypotheses

2.4.1 Conceptual Framework

The key variables, relationships and established hypotheses are shown in the framework below.

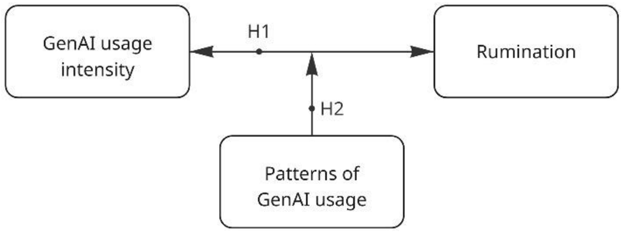

Figure 1. Conceptual Framework

2.4.2 Hypothesis 1: Degree of rumination is associated with GenAI usage duration.

Frequent and prolonged engagement with GenAI and other technology might lead to various rumination processes. Such engagement could disrupt real-world activities, social connections, or sleep patterns, all of which are known to contribute to stress and rumination (Kaewpradit et al., 2025). It also might lead to heightened cognitive load, potentially impairing the ability to manage intrusive thoughts (Singh et al., 2025). Potentially heightened AI anxiety, (Frenkenberg & Hochman, 2025), might worsen the rumination symptoms. Overall, research links excessive digital technology use to poorer mental health outcomes (Gu et al., 2022), as well as shows that mental health problems can predict technology dependence (S. Huang et al., 2024).

However, GenAI tools are used for mental health support, thus the level of rumination could be lowered. Besides, actively collaborating with GenAI instead of passively dwelling on problems, might help with processing obsessive thoughts.

Ruminators' persistent and unsuccessful search for answers might increase the use of GenAI for exploring different scenarios, possibly reinforcing the ruminative cycles (Zhang et al., 2025). Additionally, rumination might lead to increased GenAI usage by engaging in distractions and escapism. The difficulty to maintain attention from negative thoughts might extend to the difficulty to shift focus from GenAI, especially if the content engages in ruminative themes.

2.4.3 Hypothesis 2: The association between rumination and intensity of GenAI use depends on the usage patterns.

Rumination lowers self-efficacy of an individual (Gilliam, 2006), causing self-doubt. However, some rumination patterns are caused by perfectionism. Such a situation might increase reliance on GenAI for productive tasks to seek reassurance and check work meticulously to meet a higher standard. Besides, rumination undermines one's problem-solving capabilities, possibly prolonging the duration of use of this technology. The seemingly effortless way of how GenAI executes commands might lower one's confidence further, causing higher rumination levels through negative comparison and thoughts like "Why can't I handle things better?" (Treynor, 2003).

However, using GenAI for productive tasks also might have an opportunity to decrease the rumination by decreasing distress, since the tool allows for clear and structured task planning and execution that might be difficult for someone with repetitive thought patterns.

People who ruminate might also use AI as a form of a temporary distraction or escapism from distressing thoughts that they are brooding about (S. Huang et al., 2024). Distractions might help to decrease ruminative symptoms. The reflection side of rumination might also motivate individuals to use GenAI to analyze a situation or themselves in a structured way.

Given the co-occurrence of rumination with social difficulties or loneliness, some individuals might use AI for social simulation or practicing social skills (Sullivan et al., 2023). The perceived non-judgmental nature of the tools might motivate individuals to do so more.

Finally, there might be a link where intensive use of GenAI for non-productive tasks could increase rumination. It could be connected to difficulty disengaging from thoughts and the constant availability of technology to pass time.

Nonetheless, as discussed previously, actively engaging with GenAI for emotional support could also improve one's mental health, including rumination.

3. METHOD

3.1 Participants

For this study, participants were approached through convenience and volunteer sampling with snowballing effect (Hossan et al., 2023). The data collection started on the 6th of June 2025, and it was downloaded on 14th of June 2025. Because of the time constraints, large number of participants were recruited by sharing the survey link personally and asking them to forward it further. It was explicitly said that their responses will not be checked separately or right after completion, to ensure anonymity.

Important to note, the survey was conducted for a larger research project "GenAI and Mental Health", which included 3 bachelor theses, where the exclusion criteria included age under 18, non-familiarity with GenAI tools, lack of English or Dutch proficiency, having a mental health condition that could affect or be affected by participation, participation with someone and refusal to consent. By checking "I consent" box, participants marked that they consent and pass the inclusion criteria.

For this paper, participants were also filtered for their occupation and grouped in students, employed and employed students. Data entries, where demographic variables had fewer than 5 responses (e.g., "third gender / non-binary", "Prefer not to say" (gender) and "Age 60+)", were removed to improve statistical reliability and reduce the possibility of the respondent identification. This data collection resulted in an initial pool of 264 participants and a final sample of 164, as seen in Figure 1. All responses collected were answered in the English language.

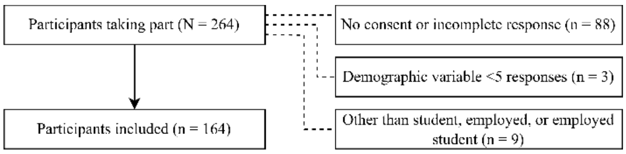

Figure 1. Visualization of the data collection procedure.

Among these participants, the majority were 18-24 years old (56.7%), genders female (53%) and male (47%) being roughly similar. The largest occupation group included students (52.4%), followed by employed (34.1%) and employed students (13.4%). The details are provided in Table 1.

Although the employed student subsample is small, it was included, since using GenAI for education or work might influence the usage intensity of each other. The findings are interpreted cautiously as exploratory.

Table 1. Descriptive Statistics (percentages rounded to one decimal).

Variable	Category	n	Percent
age	18-24	93	56.7%
age	25-29	29	17.7%
age	30-39	23	14.0%
age	40-49	13	7.9%
age	50-59	6	3.7%
gender	Male	77	47.0%
gender	Female	87	53.0%
occupation_group	Employed	56	34.1%
occupation_group	Employed Student	22	13.4%
occupation_group	Student	86	52.4%

To determine the minimum required sample size, a Power analysis was conducted using G*Power, with a medium effect size, an alpha of 0.05 and a power of 0.95. The analysis indicated that a sample of 146 would be sufficient, confirming the adequacy of the final sample size of 164. The sample was calculated for the whole "GenAI and Mental Health" project, thus the analysis included more predictors than used in this paper.

This study received approval from the Behavioral, Management and Social Sciences Ethics committee (approval number 251465).

3.2 Procedure

For this study, a quantitative structured online survey was created and hosted on Qualtrics, accessible through a web link or QR code. It was distributed through personal networks and social media platforms: WhatsApp, Instagram and LinkedIn.

Since the survey was a joint data collection method, it included more instruments than measured in this research. The data was gathered and analyzed by 3 students, where each had their own research project. Besides the relationships mentioned in the research questions of this paper, relationships of GenAI usage and loneliness or social isolation for immobile individuals and international students were investigated through this survey.

The survey began with an introduction, including short purpose of research, approximate duration, assurance of confidentiality, rights to withdraw at any time, and contact information of students conducting the research. Further, participants were asked some demographic questions, followed by a series of questionnaires to assess their personality traits, duration of GenAI use, GenAI literacy and GenAI use for different purposes. The last questionnaires were presented to participants in a random order to avoid systematic attrition of one questionnaire due to its fixed position at the end. They measured rumination, loneliness, isolation and GenAI dependency.

3.3 Materials

3.3.1 Short version of Ruminative Response Scale

Formed by Treynor et al. (2003), the short form of the Ruminative Response Scale (RRS-short or RRS-10) consists of 10 items selected from the original 22-item RRS developed by Nolen-Hoeksema & Morrow (1991). It measures ruminative tendencies by assessing two key components: brooding (5 items) and reflection (5 items) with response options rated on a 4-point Likert scale ranging from 1 ("almost never") to 4 ("almost always").

While it is a shortened version of RRS, recent studies considered it satisfactory, while increasing the convenience for participants (Erdur-Baker & Bugay, 2010; Sütterlin et al., 2012).

3.3.2 Ten-Item Personality Inventory

Gosling et al. (2003) developed Ten-Item Personality Inventory (TIPI) as a concise instrument to measure the dimensions of Big Five personality traits. It consists of 10 items (2 items per personality trait) with the response options measured on a 7-point Likert-type scale, ranging from 1 ("Disagree strongly") to 7 ("Agree strongly").

Even though TIPI has been criticized for its briefness, it is commonly used when personality is not the primary interest of the study and short measures are needed for practical reasons (Harms, 2017).

3.3.3 GenAI Literacy Scale

Formed by Gokcearslan et al. (2024), GenAI Literacy scale consists of 10 items, each scored on a 5-point Likert scale ranging from 1 ("strongly disagree" to "strongly agree"). The GenAI Literacy is measured with a total score, however 4 subscales are present: awareness, usage, evaluation and ethics.

3.3.4 GenAI Usage Duration

Recent research conducted by OpenAI and MIT Media Lab (2025) has shown that duration is a strong metric for measuring GenAI usage intensity, especially when examining its relationship with affective engagement and well-being.

For this paper, GenAI usage duration is measured in ordinal values "less than an hour", "1-3 hours per week", "4-7 hours per week", "8-15 hours per week", "More than 15 hours per week". The time window of a week was established to capture typical usage patterns, including both weekday and weekend behaviour.

3.3.5 GenAI Usage Patterns

The GenAI usage patterns are measured in 2 categories, describing productive and non-productive use.

Productive use items capture task-oriented technology uses, aligning with the utility value dimension of the Questionnaire of Artificial Intelligence Motives (Yurt & Kasarci, 2024) and principles of utilitarian information systems (Balytska et al., 2024). Productive use was assessed with items "I use GenAI for educational support" and "I use GenAI for work".

Additionally, the GenAI productive use score for "employed student" was calculated by averaging their GenAI use for academic and work purposes.

Non-productive use cases are assessed with items "I use AI tools for emotional support" and "I use AI tools to casually converse or pass time". These questions are informed by Uses and Gratifications Theory, which suggests that media and technology use is driven by fulfilment of psychological needs such as entertainment, emotional relief, or social interaction (Ruggiero, 2000). Concepts from hedonic information systems, which focus on pleasure, entertainment and intrinsically motivated interactions were consulted (Ariff et al., 2014).

GenAI usage patterns are investigated by creating different combinations of productive and non-productive use cases.

3.3.6 Control Variables

Due to their potential effect on the relationship between key variables, control variables like age (Sütterlin et al., 2012; "Three Models of Technology Adoption: A Literature Review in Brief," 2020), gender (Johnson & Whisman, 2013; Mazman et al., 2011; Stöhr et al., 2024), occupation, personality traits (Castillo-Gualda & Ramos-Cejudo, 2025; Sri et al., 2024; Zhong et al., 2024) and GenAI literacy were chosen.

3.4 Data Analysis

3.4.1 Data Preparation

Data cleaning, scoring of scales and data analysis are executed on RStudio, using R version 4.5.0.

After loading the dataset into RStudio application, data was cleaned and scores were computed for Ruminative Responses Scale – Short Form, Ten-Item Personality Inventory and GenAI Literacy scale.

3.4.2 Preliminary Statistical Analysis

The descriptive statistics of numeric and ordered ordinal variables were calculated separately. GenAI use and age are ordered ordinal variables with unequal intervals, thus they are not converted into numeric.

Later, correlation between all variables (except categorical like gender and occupation) was assessed. Variables were grouped by type and a nested loop ran all variable correlation combinations. Numeric pairs were checked with "Pearson" correlation, numeric-ordinal pairs with polyserial() method and ordinal-ordinal pairs with polychor() method. Results were rounded to 3 decimals and combined into matrix.

3.4.3 GenAI Use and Rumination

To address RQ1, a multiple linear regression analysis using lm() function in R was conducted. The dependent variable was Rumination and predictors included demographics (age, gender and occupation), personality traits, GenAI literacy and GenAI use.

3.4.4 Moderation Analysis

To address RQ2, multiple linear regression models using lm() method were created for several combinations of GenAI Use patterns: AI Productive Use only, AI Non-Productive Uses Only, Combinations of AI uses.

3.4.4.1 Exploratory Analysis

While not directly aligned with the predefined research questions, additional regressions using lm() method in R were run to better understand the contributions of GenAI use patterns to rumination. Also, the effect of GenAI Literacy subscales was investigated by applying it to Rumination subscales.

4. RESULTS

4.1 Descriptive Statistics

In this section, variable values are reported with the total score of their measurement scales. The operationalization of the variables is discussed in Appendix A.

Table 3. Descriptive statistics for numeric variables.

variable	n	mean	sd	min	max
Rumination	164	21.152	5.962	11	40
Rumination Brooding	164	11	3.498	5	20
Rumination Reflection	164	10.152	3.379	5	20
AI Productive Use	164	3.75	1.029	1	5
AI Academic Use	108	4.009	0.972	1	5
AI Work Use	78	3.346	1.067	1	5
AI Emotional Use	164	2.006	1.196	1	5
AI Casual Use	164	1.75	0.999	1	5
GenAI Literacy	164	3.638	0.551	1.75	4.833
GenAI Literacy Awareness	164	3.43	0.842	1	5
GenAI Literacy Ethics	164	3.291	0.719	1.333	5
GenAI Literacy Evaluation	164	3.854	0.749	2	5
GenAI Literacy Usage	164	3.979	0.88	1	5
Extraversion	164	4.162	1.43	1	7
Agreeableness	164	4.726	1.141	1.5	7
Conscientiousness	164	5.174	1.243	1.5	7
Emotional Stability	164	4.473	1.358	1	7
Openness	164	5.137	1.043	1.5	7

In Table 3., the total rumination score is approx. 21.15, suggesting moderate overall rumination, where brooding and reflection subscales are rather balanced. Most personality traits cluster around 4 and 5, suggesting average tendencies.

On GenAI literacy scale, respondents scored moderately high (mean ≈ 3.64) and consistent across participants (SD ≈ 0.55). Participants feel confident using AI tools (GenAI Literacy Usage ≈ 3.98), however we observe some slight lack of ethical considerations (GenAI Literacy Ethics mean ≈ 3.29).

By observing using AI for productive tasks like education or work support, AI Academic Use is the most common (mean ≈ 4.009).

Most participants do not use AI for emotional support (mean ≈ 2) or to casually pass time (mean = 1.75).

Table 4. Descriptive statistics for the ordinal variable – GenAI Use Duration.

GenAI Use (weekly)	n	Percent
Less than 1h	32	19.5%
1-3h	59	36.0%
4-7h	42	25.6%
8-15h	23	14.0%
More than 15h	8	4.9%

Most participants (36%) use GenAI tools from 1 to 3 hours per week and only 4.9% use them heavily, more than 15 hours per week.

4.2 Correlation

A correlation analysis between all variables (except categorical variables occupation and gender) was conducted and can be observed in Appendix B). High correlation between scales and their subscales are there as expected, not relevant.

AI Casual Use and AI Emotional Use moderately correlated ($r \approx 0.67$), suggesting that individuals who use AI for emotional support, also tend to use it to casually pass time. This correlation is considered in interpretation.

Notably, higher rumination was weakly correlated with lower emotional stability ($r \approx -0.43$) and conscientiousness ($r \approx -0.28$). Also, higher rumination showed weak correlation with higher AI use for emotional support ($r \approx 0.35$) and AI use to casually pass time use ($r \approx 0.33$). From these, Rumination's subscale Reflection showed stronger correlation with AI use for emotional support ($r \approx 0.42$) than brooding ($r \approx 0.19$), likely connected to the self-analyzing nature of reflection (Loerakker et al., 2024; Watkins, 2008).

The correlation between GenAI use had weak negative relationships with all the GenAI use cases observed (academic, work, casual and emotional).

GenAI literacy showed little to no relation with GenAI Use ($r \approx - 0.1$), suggesting that respondents did not feel more confident in using GenAI tools, when using them for longer durations of time. They might have felt slightly less confident.

Notably, age showed a negative weak correlation with GenAI literacy ($r \approx -0.27$) and a negative weak correlation with the subscale "Usage" specifically ($r \approx -0.35$), suggesting that the younger population scored higher on GenAI literacy and self-perceived competence in practical application of GenAI tools. Age has a moderate negative correlation with AI use for academic support ($r \approx -0.47$), which is expected, since students are usually within the younger subsample.

4.3 GenAI Use and Rumination

To answer the first research question, a multiple linear regression was executed. The statistics of the model (See Appendix C, Table 6.) show that the model explains approximately 22.3% of the variance in rumination scores after adjusting for the number of predictors. With $F(17, 146)$ 3.75, $p < .001$, the model proves to be statistically significant.

The results of multiple linear regression (see Appendix C, Table 7.) did not indicate a relationship between GenAI Use duration and rumination, when controlling for age, gender, occupation, personality traits and GenAI literacy. Similarly, these control variables did not show any significant association. However, emotional stability ($\beta \approx -1.3$, $p < 0.001$) and extraversion ($\beta \approx -0.92$, $p < 0.05$) were significant negative predictors of rumination.

4.4 GenAI Usage Patterns moderating GenAI Usage Duration and Rumination

In this section, various GenAI Use patterns were investigated by combining GenAI Use cases differently. Although the variables were changed, the variance models explained were roughly similar, when at least 2 use cases are added, as can be seen in Table 8.

Table 8. Statistics of Moderation Models

Model	R^2	Adjusted R^2	F Statistic	DF1	DF2	P Value	N
Moderation Model: GenAI Use × AI Productive Use on Rumination	0.3244	0.2190	3.0770	22	141	3.11E-05	164
Moderation Model: GenAI Use × Non-Productive uses on Rumination	0.4572	0.3495	4.2429	27	136	9.76E-09	164
Moderation Model: GenAI Use × AI all use cases on Rumination	0.4821	0.3556	3.8106	32	131	3.27E-08	164
Moderation Model: GenAI Use × AI Productive Use, GenAI Use × AI Emotional Use	0.4301	0.317	3.802	27	136	1.28EE-07	164
Moderation Model: GenAI Use × AI Productive Use, GenAI Use × AI Casual Use	0.449	0.3396	4.105	27	136	2.17E-06	164

4.4.1 AI Productive Use as Moderator

To investigate the interaction between GenAI Use weekly duration and AI Productive Use, multiple linear regression was run, and the results can be seen in **Appendix D.** AI Productive Use did not have a significant main or interaction effect ($p > 0.05$).

Extraversion ($\beta \approx -0.94$, $p < 0.05$), Conscientiousness ($\beta \approx -0.8388$, $p < 0.05$) and Emotional Stability ($\beta \approx -1.31$, $p < 0.001$) are again significant predictors of Rumination.

4.4.2 AI Non-Productive Use as Moderator

As seen in Table 10, when investigating the Non-Productive Use pattern, excluding AI Productive Use, AI Emotional Use was a significant predictor of Rumination ($\beta \approx 2.05$, $p < 0.05$), as well as it showed a significant interaction for individuals using GenAI 4-7 hours per week ($\beta \approx -2.41$, $p < 0.05$).

While AI Casual Use was not significant on its own, a significant interaction was found for AI Casual Use among individuals using GenAI 4-7 hours per week ($\beta \approx 2.97$, $p < 0.05$).

Extraversion ($\beta \approx -0.8$, $p < 0.05$), Emotional Stability ($\beta \approx -1.54$, $p < 0.001$) were strong predictors of Rumination.

Table 10. Moderation Model: GenAI Use × Non-Productive Use on Rumination.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**23.0490**	**4.3101**	**5.3477**	**3.67E-07**
GenAI Use 4-7h	1.3366	2.2613	0.5911	0.5554
GenAI Use 8-15h	2.1246	2.5103	0.8464	0.3988
GenAI Use Less than 1h	-0.3289	2.8483	-0.1155	0.9082
GenAI Use More than 15h	-5.0102	5.6100	-0.8931	0.3734
AI Casual Use	0.0181	0.8986	0.0201	0.9840
AI Emotional Use	**2.0524**	**0.7329**	**2.8002**	**0.0059**
GenAI Literacy	0.2144	0.8304	0.2581	0.7967
Extraversion	**-0.8023**	**0.2926**	**-2.7420**	**0.0069**
Agreeableness	-0.2514	0.3625	-0.6936	0.4891
Conscientiousness	-0.3322	0.3807	-0.8726	0.3844
Emotional Stability	**-1.5380**	**0.3173**	**-4.8466**	**3.38E-06**
Openness	0.7875	0.4546	1.7323	0.0855
age 25-29	-0.9837	1.1274	-0.8726	0.3844
age 30-39	-0.2937	1.7671	-0.1662	0.8683
age 40-49	0.9585	2.0402	0.4698	0.6392
age 50-59	-0.3078	2.5674	-0.1199	0.9048
gender Male	-0.8472	0.8492	-0.9976	0.3203
occupation group Employed Student	2.9826	1.7724	1.6828	0.0947
occupation group Student	2.5285	1.4864	1.7012	0.0912
GenAI Use 4-7h & AI Casual Use	**2.9692**	**1.3286**	**2.2347**	**0.0271**
GenAI Use 8-15h & AI Casual Use	1.5225	1.5663	0.9721	0.3327
GenAI Use Less than 1h & AI Casual Use	0.6628	1.7879	0.3707	0.7114
GenAI Use More than 15h & AI Casual Use	2.8763	3.5915	0.8008	0.4246
GenAI Use 4-7h & AI Emotional Use	**-2.4095**	**1.1045**	**-2.1815**	**0.0309**
GenAI Use 8-15h & AI Emotional Use	-1.2150	1.2731	-0.9544	0.3416
GenAI Use Less than 1h & AI Emotional Use	1.1144	2.5260	0.4412	0.6598
GenAI Use More than 15h & AI Emotional Use	0.3770	4.3209	0.0872	0.9306

4.4.3 Mix of Productive and Non-Productive Uses as Moderators

As seen in Table 11., when investigating the Use Pattern of all use cases (AI Productive Use, AI Casual Use and AI Emotional Use), AI Emotional Use was significant as a main effect predictor ($\beta \approx 1.86$, $p < 0.05$) and interaction term with GenAI Use 4-7 hours weekly ($\beta \approx 2.7$, $p < 0.05$).

Personality traits like Extraversion ($\beta \approx -0.84$, $p < 0.05$) and Emotional Stability ($\beta \approx -1.55$, $p < 0.001$) continue to be strong negative predictors of rumination.

Table 11. Moderation Model: GenAI Use × AI all use cases on Rumination.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**22.2476**	**5.0269**	**4.4257**	**2.00E-05**
GenAI Use 4-7h	3.4938	6.1853	0.5649	0.5731
GenAI Use 8-15h	11.4952	7.3627	1.5613	0.1209
GenAI Use Less than 1h	1.2436	4.9879	0.2493	0.8035
GenAI Use More than 15h	-20.6402	10.4886	-1.9679	0.0512
AI Productive Use	0.5098	0.8060	0.6324	0.5282
AI Casual Use	0.2386	0.9371	0.2547	0.7994
AI Emotional Use	**1.8562**	**0.7748**	**2.3957**	**0.0180**
GenAI Literacy	-0.0616	0.8474	-0.0727	0.9422
Extraversion	**-0.8365**	**0.2924**	**-2.8607**	**0.0049**
Agreeableness	-0.2478	0.3686	-0.6722	0.5026
Conscientiousness	-0.3846	0.3908	-0.9841	0.3269
Emotional Stability	**-1.5491**	**0.3182**	**-4.8683**	**3.18E-06**
Openness	0.8574	0.4636	1.8492	0.0667
age 25-29	-0.6608	1.1375	-0.5809	0.5623
age 30-39	-0.3289	1.7953	-0.1832	0.8549
age 40-49	0.8193	2.0696	0.3959	0.6928
age 50-59	-0.5759	2.6122	-0.2205	0.8259
gender Male	-0.8612	0.8559	-1.0061	0.3162
occupation group Employed Student	2.9430	1.7773	1.6559	0.1001
occupation group Student	2.6323	1.5009	1.7538	0.0818
GenAI Use 4-7h & AI Productive Use	-0.5648	1.3108	-0.4308	0.6673
GenAI Use 8-15h & AI Productive Use	-2.0765	1.5414	-1.3472	0.1803
GenAI Use Less than 1h & AI Productive Use	-0.3822	1.2993	-0.2942	0.7691
GenAI Use More than 15h & AI Productive Use	3.2201	1.9922	1.6164	0.1084
GenAI Use 4-7h & AI Casual Use	**2.6951**	**1.3536**	**1.9910**	**0.0486**
GenAI Use 8-15h & AI Casual Use	0.9494	1.6137	0.5883	0.5573
GenAI Use Less than 1h & AI Casual Use	0.5494	1.8214	0.3016	0.7634
GenAI Use More than 15h & AI Casual Use	8.2119	4.4987	1.8254	0.0702
GenAI Use 4-7h & AI Emotional Use	-2.2284	1.1672	-1.9092	0.0584
GenAI Use 8-15h & AI Emotional Use	-0.9235	1.2990	-0.7109	0.4784
GenAI Use Less than 1h & AI Emotional Use	1.0937	2.5310	0.4321	0.6664
GenAI Use More than 15h & AI Emotional Use	-3.6146	4.8082	-0.7518	0.4535

4.4.3.1 Combinations of AI Productive Use and Non-Productive Use cases separately

Multilinear regression with interaction terms AI Productive Use and AI Emotional Use, did not show any significant interactions, as is summarized in **Appendix E.** Notably, AI Emotional Use ($\beta \approx 1.93$, $p < 0.001$), Extraversion ($\beta \approx -0.81$, $p < 0.05$) and Emotional Stability ($\beta \approx -1.48$, $p < 0.001$) were significant predictors of Rumination.

As demonstrated in **Table 13,** we also investigated interactions of GenAI weekly use and AI Productive Use, and AI Casual Use. AI Productive Use was not significant, however AI Casual Use was significant as a main effect ($\beta \approx 1.8$, $p < 0.05$) and as an interaction GenAI Use More than 15 hours per week ($\beta \approx 5.27$, $p < 0.05$).

Extraversion ($\beta \approx -0.8$, $p < 0.05$) and Emotional Stability ($\beta \approx -1.55$, $p < 0.001$) are strong negative predictors.

Table 13. Moderation Model: GenAI Use × AI Productive Use, GenAI Use × AI Casual Use.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**22.4206**	**5.0066**	**4.4782**	**1.58E-05**
GenAI Use 4-7h	3.7828	5.7638	0.6563	0.5127
GenAI Use 8-15h	12.5747	7.4296	1.6925	0.0928
GenAI Use Less than 1h	4.5558	4.6560	0.9785	0.3296
GenAI Use More than 15h	-19.7546	10.5348	-1.8752	0.0629
AI Productive Use	1.2002	0.7679	1.5628	0.1204
AI Casual Use	**1.8018**	**0.6802**	**2.6490**	**0.0090**
GenAI Literacy	-0.2941	0.8409	-0.3498	0.7271
Extraversion	**-0.8355**	**0.2919**	**-2.8619**	**0.0049**
Agreeableness	-0.3566	0.3656	-0.9755	0.3310
Conscientiousness	-0.3965	0.3883	-1.0212	0.3090
Emotional Stability	**-1.5143**	**0.3205**	**-4.7251**	**5.67E-06**
Openness	0.8027	0.4558	1.7610	0.0805
age 25-29	-0.6720	1.1394	-0.5898	0.5563
age 30-39	-0.2583	1.7927	-0.1441	0.8856
age 40-49	0.5153	2.0655	0.2495	0.8034
age 50-59	-0.2377	2.5924	-0.0917	0.9271
gender Male	-0.9559	0.8340	-1.1462	0.2537
occupation group Employed Student	2.7098	1.7487	1.5496	0.1236
occupation group Student	2.9114	1.4833	1.9628	0.0517
GenAI Use 4-7h & AI Productive Use	-1.1156	1.2448	-0.8962	0.3717
GenAI Use 8-15h & AI Productive Use	-2.5732	1.5315	-1.6802	0.0952
GenAI Use Less than 1h & AI Productive Use	-1.1017	1.2850	-0.8574	0.3928
GenAI Use More than 15h & AI Productive Use	2.3798	1.8153	1.3110	0.1921
GenAI Use 4-7h AI Casual Use	0.8536	1.0553	0.8089	0.4200
GenAI Use 8-15h & AI Casual Use	0.2139	1.1422	0.1873	0.8517
GenAI Use Less than 1h & AI Casual Use	0.2507	1.3723	0.1827	0.8553
GenAI Use More than 15h & AI Casual Use	**5.2655**	**2.3599**	**2.2313**	**0.0273**

4.5 Exploratory Analysis

4.5.1 GenAI Use Patterns and Rumination

The multiple regression model investigating the association between GenAI use patterns and Rumination explains approximately 34%, when accounted for control variables. The GenAI Use patterns included all use cases, including AI Productive, Casual Use and Emotional Use. The model is statistically significant with $F(16, 147) = 6.31$, $p < .001$, with a total sample size of 164, for model statistic see Appendix F, Table 14.

In Appendix F, Table 15, we see that AI Casual Use was a significant predictor of rumination ($\beta \approx 1.5$, $p < 0.05$), suggesting that higher casual use of AI is associated with higher rumination. Personality traits like extraversion and emotional stability were negatively associated with rumination. Also, employed individuals were associated with lower rumination ($\beta \approx -2.83$, $p < 0.05$) compared to students, scoring almost 2 points lower on rumination score.

4.5.2 GenAI Use, Use Patterns and Rumination

When Rumination is predicted using both GenAI Use, GenAI Use patterns, and a set of control variables, the model explains approximately 35%, when adjusted for the number of predictors (See Appendix G, Table 16). It shows a very small increase from the previous regressions that included the AI use patterns only. The model is statistically significant with $F(16, 147) = 6.31$, $p < .001$.

Similarly to the previous model investigating the relationship between GenAI Use Patterns and Rumination, scoring higher on Extraversion ($\beta \approx -0.9$, $p < 0.05$) and Emotional stability ($\beta \approx -1.4$, $p < 0.001$), and being in the "Employed" group ($\beta \approx -3$, $p < 0.05$), were associated with lower rumination.

Even though GenAI Use categories are not statistically significant, including this variable in the model allows to reveal the contribution of AI Emotional Use ($\beta \approx 0.99$, $p < 0.05$), which was not apparent previously due to their shared variance.

Both non-productive uses AI Emotional Use ($\beta \approx 0.99$, $p < 0.05$) and AI Casual Use ($\beta \approx -1.49$, $p < 0.05$) are positively related to Rumination.

4.5.3 The Importance of GenAI Literacy, Non-Productive use and Reflection

In this result section, the importance of GenAI Literacy is investigated. GenAI Literacy's subscale "Evaluation" was a significant predictor for Rumination's subscale "Reflection".

When assessing how non-productive use patterns predict reflection, GenAI Literacy's subscale Evaluation was a significant positive predictor of Reflection (see Appendix H).

5. DISCUSSION

5.1 Summary and Interpretation of Results

Several models were run to investigate the hypotheses, as well as explore different relationships between variables, in order to gain deeper understanding of how GenAI use associates with Rumination and its dimensions.

5.1.1 Hypothesis 1

The initial hypothesis (H1) proposed that different levels of GenAI Use intensity (measured by duration of use) are associated with different rumination levels. However, after analyzing data, we found that there is no significant relationship between GenAI use and rumination, when controlling for control variables. It also might be that the time-based measure is not sufficiently a standalone predictor of rumination, and it could be beneficial for other variables to be considered.

5.1.2 Hypothesis 2

Hypothesis 2 (H2) proposed that the relationship between GenAI usage and rumination is moderated by the way the GenAI tool is used. We partially accept this hypothesis.

5.1.2.1 GenAI for Productive Use patterns as Predictor of Rumination

Using GenAI for productive use (academic, work or both) alone or together with other use cases, was not a significant predictor of rumination, when observed in interaction with GenAI Use. Productive tasks are output-oriented (Autor, 2013), focused on external output rather than on the internal state. It might be the reason why AI productive use has no association with rumination. Also, it is not clear if GenAI use is associated with lower self-efficacy like rumination (Gilliam, 2006), since the survey questions were built with the utility value of technology in mind rather than how it makes one feel.

5.1.2.2 GenAI for Non-Productive Use patterns as Predictor of Rumination

When GenAI tools are used for Non-Productive Use purposes (see Table 10), AI use for emotional support shows to be a significant positive predictor of rumination ($\beta \approx 2.05$, $p < 0.05$). It aligns with current literature, where rumination is linked to more intense technology usage (Gao & Du, 2025; Hu et al., 2023). Additionally, rumination can co-occur with loneliness (Sullivan et al., 2023), thus higher usage of GenAI for emotional support might suggest usage of GenAI for social simulation or companionship (Morales-Garcia et al., 2024; Skjuve et al., 2024).

Nevertheless, there is a seemingly contradicting finding. Individuals using GenAI for 4-7 hours per week, when interacting with GenAI use for emotional support were associated with significantly lower rumination ($\beta \approx -2.41$, $p < 0.05$). The window between 4 to 7 hours might be the optimal intensity of GenAI use, where one might benefit from the accessible support for mental health (Khawaja & Bélisle-Pipon, 2023), while not overly relying or depending on it.

Notably, in the same model, while 4-7 hours of weekly GenAI use, in interaction with using GenAI for emotional support, was linked to lower rumination, the same duration, when interacting with causal GenAI use, showed a positive association with rumination ($\beta \approx 2.97$, $p < 0.05$). It suggests that the purpose of use is important even when the duration of interaction is moderate.

5.1.2.3 Productive and Non-Productive Use patterns as predictors of Rumination

In Moderation Model, investigating interactions between GenAI Use and all AI use patterns (see Table 11), we see that the Productive Use is not significant to predicting Rumination. However, including it in the model removed an interaction of using GenAI for 4 to 7 hours per week and AI Emotional Use ($\beta \approx 2.97$, $p < 0.05$) that was significant in the model of using GenAI for non-productive use only (Table 10).

It is plausible that individuals who engage in moderate use of GenAI for emotional support, also use it for productive purposes. The "AI Productive Use" might be capturing some variance of the active engagement that was previously attribute to the moderate emotional use interaction exclusively. The positive cognitive effects of using GenAI (Moongela et al., 2024; Zhou et al., 2024) might be apparent across productive and adaptive moderate emotional uses of AI. The underlying cognitive benefits of active engagement with GenAI might be share across both categories.

5.1.3 Personality Traits, Occupation and Rumination

Personality traits like Emotional Stability and Extraversion consistently showed to be strong negative predictors of rumination. It supports the current literature, stating that individuals higher in Emotional Stability (often referred to as the opposite of neuroticism) and Extraversion tend to experience lower levels of rumination (Slavish et al. 2017; Castillo-Gualda & Ramos-Cejudo, 2025).

Additionally, in the exploratory multiple linear regression for GenAI Use Patterns and Rumination (see Table 15. In Appendix F) it showed that being in the "employed" group was associated with lower rumination ($\beta \approx -2.83$, $p < 0.05$). The difference in rumination levels was even lower, when accounting for GenAI Use duration ($\beta \approx -3.01$, $p < 0.05$), as seen in Appendix G, Table 17. It might suggest that being in a more structured environment and facing different types of stressors might influence the rumination levels.

5.1.4 Importance of GenAI Literacy and Reflection

GenAI Literacy scale was not a significant predictor of Rumination. For exploratory purposes, we investigated the relationship between its subscales and Rumination subscales.

GenAI Literacy's "Evaluation" subscale showed to be a significant positive predictor of Reflection, when GenAI tool is used for emotional use, casual use, or both. Reflection involves attempting to understand one's feelings or situation (Watkins, 2008). This finding suggests that people confident in evaluating GenAI content may engage with GenAI in more reflective thought processes. When both Non-productive uses are included in the model, emotional use was significant ($\beta \approx 0.95$, $p < 0.001$), but casual use was not, when also controlling for GenAI Literacy Evaluation ($\beta \approx 1.15$, $p < 0.05$). This aligns with the self-analysis aspect of reflection, where individuals might write down thoughts to analyze them (Watkins, 2008).

5.2 Theoretical Contributions

This paper contributes to the research of rumination within the field of Human-AI Interactions. The research addresses the research gap described in the introduction. It suggests that findings from older technology cannot be simply transferred to GenAI. The distinction between productive and non-productive uses of GenAI adds context on how different digital interactions associate with rumination (Michl et al., 2013; Watkins & Roberts, 2020).

A key theoretical contribution is the finding that GenAI Use intensity (measured in duration) is not a significant direct predictor of rumination by itself. However, the patterns of its usage have significant association with rumination. It emphasizes that while GenAI offer cognitive off-loading utility (Gerlich, 2025) and a place for accessible and non-judgmental emotional support (Chan, 2025; Y. Wang et al., 2025), the way they are used play a significant role.

Finally, the positive relationship between GenAI Literacy's "Evaluation" and Rumination's "Reflection", provides a new theoretical insight.

5.3 Practical Implications

Firstly, during this research, it was consistently shown that the intensity or duration of GenAI use alone does not predict rumination, however, the purpose and patterns of use are important. The users should focus on the way they use the tools rather than simply on their use time.

Secondly, mental health professionals can gain insights into their patients' ruminative tendencies by asking them about their regular interactions with GenAI tools. It might be beneficial, since rumination is a symptom of several mental disorders (Ehring, 2021).

Moreover, design or usage strategies that account for user personality differences could help promote sustainable and healthy interactions with the tools.

Finally, we observed that there were no negative associations between GenAI use for emotional support and rumination. Thus, we cannot advise using GenAI tools for this purpose, even if literature suggests that it offers several benefits.

5.4 Limitations

Firstly, the study uses a cross-sectional survey, capturing self-reported data at a single point in time, preventing exploration of causal relationships or introducing bias. Besides, no qualitative data was gathered on how or why individuals interact with GenAI in an emotionally significant way.

Secondly, the sample was skewed toward students and young adults, mostly recruited through convenience and snowball sampling, which not only introduced selection bias, but also limited diversity in occupations. Many "employed students" blur the group comparisons. Additionally, a larger sample would increase the generalizability of results.

5.5 Future Direction

This paper has explored the associations between rumination, Genai and its usage patterns, however causality needs to be further investigated. Longitudinal or experimental designs might help to understand the effect one has on the other.

Simple use-cases were investigated, however user motivation to use them were not. Psychological and cognitive experiences while using GenAI tools would explain when, why and how people use GenAI and how they feel about it. Besides, different tools offer different experiences, advantages and disadvantages, thus it would be valuable to investigate how specific tools or response styles affect user well-being.

The relationship between different use patterns and subsamples differed, thus it is crucial to investigate the cause of such results to make them applicable and useful.

Since GenAI is entering the everyday life of a large population and is accessible almost constantly, it is important to also assess habit formation or overuse, as well as explore ethical and design questions to promote healthy use and reduce risks of reinforcing unhealthy usage patterns.

6. CONCLUSION

This study investigated the relationship between GenAI Use and rumination. We investigated both the intensity of GenAI use and rumination, as well as how the productive and non-productive patterns of GenAI use changed this relationship.

The findings show that GenAI Use Intensity was not directly associated with Rumination, suggesting that simply focusing on the duration of GenAI use is not sufficient to gain significant insights about one's rumination levels. However, the patterns of GenAI Use were proven to have significant relationship with rumination levels.

Productive uses of GenAI, including using GenAI for academic purposes, work purposes or both) did not show significant association with rumination levels. Whereas non-productive uses of GenAI, including using it casually pass time or for emotional support, were positively linked to higher rumination.

Casual GenAI use, characterized as engaging with GenAI to pass time, showed a significant positive association with rumination. This indicates that aimless interaction with GenAI has a positive relationship with rumination.

Also, engaging with GenAI for emotional support was positively significantly associated with rumination levels. It might suggest that people with ruminative tendencies might use GenAI human-like conversational abilities to seek help.

Beyond GenAI use and the usage patterns, this paper has highlighted the importance of individual characteristics like personality traits and occupation. Emotional stability and extraversion had a consistent significant negative association with rumination, which aligns with the existing literature. Furthermore, being employed (excluding employed students) was associated with lower rumination than students in several models.

Finally, through exploratory analysis, we found that GenAI Literacy's subscale "Evaluation" was associated with higher levels of Rumination's subscale "Reflection".

In conclusion, this study shows that the relationship between rumination and GenAI use cannot be assessed simply through the time of engagement. The purpose of interaction, individual personality traits and life contexts or professional environment are important to consider. These findings provide a basis for future research to investigate the contextual factors in the relationship of GenAI use and rumination, as well as promoting the importance of designing tools and strategies that consider individual differences.

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8. APPENDICES

8.1 Appendix A

Table 2. Variable Operationalization.

Variable	Measurement	Description
GenAI Use	Estimated average GenAI use duration per week, Ordinal Variable	"Less than an hour per week", "1-3 hours per week", "4-7 hours per week", "8-15 hours per week", "More than 15 hours per week".
Rumination	Ruminative Response Scale Short (RRS-short) (Treynor et al., 2003)	Subscales: Brooding, Reflection.
Personality traits	Ten-Item Personality Inventory (Gosling et al., 2003)	Subscales: Extraversion, Agreeableness, Conscientiousness, Emotional Stability, Openness.
GenAI Literacy	GenAI Literacy scale (Gokcearslan et al., 2024)	Subscales: Awareness, Usage, Evaluation, Ethics.
Productive Use	Productive use, Numeric variable	AI Academic Use values for students, AI Work Use values for employed, average value of AI Academic Use and AI Work Use for employed students.
	AI Academic Use, Numeric variable	"I use AI tools for academic support."
	AI Work Use, Numeric variable	"I use AI tools for work."
Non-Productive Use	AI, Emotional Use, Numeric variable	"I use AI for emotional support."
	AI Casual Use, Numeric variable	"I use AI tools to casually converse or pass time."
Age	Ordinal Variable	"18-24", "25-29", "30=39", "40-49", "50-59", "60+".
Gender	Categorical Variable	Female, Male (Non-binary/third gender and "Prefer not to say" not included in the analysis).
Occupation	Categorical Variable	Student, Employed, Employed Student.

8.2 Appendix B

Table 5. Correlation Matrix.

	Rumination	Rumination Brooding	Rumination Reflection	Extra-version	Agree-ableness	Conscien-tiousness	Emotional Stability	Openness	GenAI Literacy	GenAI Literacy Awareness	GenAI Literacy Usage	GenAI Literacy Evaluation	GenAI Literacy Ethics	AI Academic Use	AI Work Use	AI Emotional Use	AI Casual Use	GenAI Use	age
Rumination	1	0.872	0.862	-0.323	0.026	-0.282	-0.427	-0.094	-0.001	-0.134	0.01	0.122	0.014	0.132	0.122	0.354	0.333	-0.025	-0.189
Rumination Brooding	0.872	1	0.503	-0.307	0.046	-0.217	-0.511	-0.128	0.019	-0.13	0.035	0.084	0.08	0.173	0.081	0.194	0.269	-0.022	-0.152
Rumination Reflection	0.862	0.503	1	-0.253	-0.002	-0.274	-0.224	-0.033	-0.021	-0.102	-0.019	0.128	-0.057	0.054	0.132	0.423	0.309	-0.022	-0.176
Extraversion	-0.323	-0.307	-0.253	1	-0.012	0.202	0.252	0.158	0.003	0.097	0.031	-0.057	-0.082	-0.015	0.057	-0.128	-0.124	0.185	0.098
Agreeableness	0.026	0.046	-0.002	-0.012	1	0.039	0.025	0.19	0.147	0.039	0.185	0.184	-0.014	0.096	0.071	0.051	0.009	0.07	-0.117
Conscientiousness	-0.282	-0.217	-0.274	0.202	0.039	1	0.321	0.373	0.23	0.019	0.249	0.245	0.123	0.007	0.133	-0.207	-0.298	0.118	0.015
Emotional Stability	-0.427	-0.511	-0.224	0.252	0.025	0.321	1	0.194	0.118	0.147	0.132	0.055	-0.029	0.013	0.12	-0.087	-0.093	0.069	0.056
Openness	-0.094	-0.128	-0.033	0.158	0.19	0.373	0.194	1	0.274	0.104	0.339	0.251	0.041	0.089	0.041	-0.262	-0.353	0.105	-0.204
GenAI Literacy	-0.001	0.019	-0.021	0.003	0.147	0.23	0.118	0.274	1	0.734	0.696	0.81	0.511	0.267	0.243	-0.088	-0.187	-0.095	-0.27
GenAI Literacy Awareness	-0.134	-0.13	-0.102	0.097	0.039	0.019	0.147	0.104	0.734	1	0.28	0.406	0.314	0.1	0.027	-0.122	-0.112	-0.114	-0.167
GenAI Literacy Usage	0.01	0.035	-0.019	0.031	0.185	0.249	0.132	0.339	0.696	0.28	1	0.596	-0.04	0.395	0.412	-0.058	-0.184	-0.044	-0.351
GenAI Literacy Evaluation	0.122	0.084	0.128	-0.057	0.184	0.245	0.055	0.251	0.81	0.406	0.596	1	0.237	0.331	0.338	-0.013	-0.12	-0.142	-0.273
GenAI Literacy Ethics	0.014	0.08	-0.057	-0.082	-0.014	0.123	-0.029	0.041	0.511	0.314	-0.04	0.237	1	-0.128	-0.145	-0.043	-0.092	0.045	0.082
AI Academic Use	0.132	0.173	0.054	-0.015	0.096	0.007	0.013	0.089	0.267	0.1	0.395	0.331	-0.128	1	0.392	-0.042	-0.143	-0.042	-0.474
AI Work Use	0.122	0.081	0.132	0.057	0.071	0.133	0.12	0.041	0.243	0.027	0.412	0.338	-0.145	0.392	1	0.12	0.012	-0.116	-0.18
AI Emotional Use	0.354	0.194	0.423	-0.128	0.051	-0.207	-0.087	-0.262	-0.088	-0.122	-0.058	-0.013	-0.043	-0.042	0.12	1	0.674	-0.242	0.037
AI Casual Use	0.333	0.269	0.309	-0.124	0.009	-0.298	-0.093	-0.353	-0.187	-0.112	-0.184	-0.12	-0.092	-0.143	0.012	0.674	1	-0.125	0.256
GenAI Use	-0.025	-0.022	-0.022	0.185	0.07	0.118	0.069	0.105	-0.095	-0.114	-0.044	-0.142	0.045	-0.042	-0.116	-0.242	-0.125	1	0.112
age	-0.189	-0.152	-0.176	0.098	-0.117	0.015	0.056	-0.204	-0.27	-0.167	-0.351	-0.273	0.082	-0.474	-0.18	0.037	0.256	0.112	1

8.3 Appendix C

Table 6. Multiple Linear Regression for GenAI Use and Rumination.

R^2	Adjusted R^2	F Statistic	DF1	DF2	P Value	N
0.3038	0.2227	3.747	17	146	5.76E-06	164

Table 7. Multiple Linear Regression for GenAI Use and Rumination.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**33.3628**	**4.299**	**7.7606**	**1.35E-12**
GenAI Use 1-3h	-0.235	1.2295	-0.1912	0.8487
GenAI Use 4-7h	0.7315	1.3589	0.5383	0.5912
GenAI Use 8-15h	1.8411	1.5191	1.2119	0.2275
GenAI Use More than 15h	1.245	2.1636	0.5754	0.5659
GenAI Literacy	0.0757	0.8762	0.0865	0.9312
age 25-29	-0.7745	1.2097	-0.6402	0.5231
age 30-39	0.1138	1.8521	0.0614	0.9511
age 40-49	0.6461	2.1527	0.3001	0.7645
age 50-59	-1.1658	2.7105	-0.4301	0.6677
gender Female	1.3585	0.8826	1.5392	0.1259
Extraversion	**-0.9239**	**0.312**	**-2.9617**	**0.0036**
Agreeableness	-0.0407	0.3852	-0.1056	0.916
Conscientiousness	-0.7532	0.3961	-1.9017	0.0592
Emotional Stability	**-1.3025**	**0.34**	**-3.8312**	**0.0002**
Openness	0.1822	0.4665	0.3905	0.6967
occupation group Employed Student	-0.2877	1.3331	-0.2158	0.8294
occupation group Employed	-1.9145	1.5332	-1.2487	0.2138

8.4 Appendix D

Table 9. Interaction Model: GenAI Use x AI Productive Use on Rumination

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**28.7541**	**4.8942**	**5.8752**	**2.91E-08**
GenAI Use 4-7h	7.9676	5.3308	1.4947	0.1372
GenAI Use 8-15h	11.2196	7.1568	1.5677	0.1192
GenAI Use Less than 1h	4.7716	4.5866	1.0403	0.3
GenAI Use More than 15h	-0.711	7.0262	-0.1012	0.9195
AI Productive Use	1.1399	0.8322	1.3698	0.1729
GenAI Literacy	0.016	0.8959	0.0179	0.9857
Extraversion	**-0.9354**	**0.3141**	**-2.9783**	**0.0034**
Agreeableness	-0.0959	0.3942	-0.2433	0.8082
Conscientiousness	-0.8388	0.4098	-2.0471	0.0425
Emotional Stability	**-1.3116**	**0.3429**	**-3.8248**	**0.0002**
Openness	0.3345	0.4809	0.6956	0.4879
age 25-29	-0.6662	1.2255	-0.5436	0.5875
age 30-39	0.145	1.9173	0.0756	0.9398
age 40-49	0.7353	2.2071	0.3332	0.7395
age 50-59	-1.5787	2.7683	-0.5703	0.5694
gender Male	-1.3285	0.8924	-1.4886	0.1388
occupation group Employed Student	1.4452	1.8685	0.7734	0.4406
occupation group Student	1.7649	1.581	1.1163	0.2662
GenAI Use 4-7h & AI Productive Use	-1.8265	1.3113	-1.3929	0.1658
GenAI Use 8-15h & AI Productive Use	-2.2416	1.6317	-1.3738	0.1717
GenAI Use Less than 1h & AI Productive Use	-1.2905	1.3921	-0.927	0.3555
GenAI Use More than 15h & AI Productive Use	0.4965	1.7492	0.2839	0.7769

8.5 Appendix E

Table 12. Moderation Model: GenAI Use × Non-Productive uses on Rumination

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**23.6504**	**4.7766**	**4.9513**	**2.15E-06**
GenAI Use 4-7h	5.7405	6.1399	0.9349	0.3515
GenAI Use 8-15h	11.7581	7.0837	1.6599	0.0992
GenAI Use Less than 1h	1.3477	4.9721	0.2711	0.7868
GenAI Use More than 15h	-12.2759	9.3367	-1.3148	0.1908
AI Productive Use	0.5527	0.7963	0.6940	0.4888
AI Emotional Use	**1.9326**	**0.5717**	**3.3806**	**0.0009**
GenAI Literacy	-0.1331	0.8689	-0.1532	0.8785
Extraversion	**-0.8077**	**0.2999**	**-2.6932**	**0.0080**
Agreeableness	-0.2416	0.3752	-0.6440	0.5207
Conscientiousness	-0.5273	0.3896	-1.3534	0.1782
Emotional Stability	**-1.4773**	**0.3247**	**-4.5503**	**1.18E-05**
Openness	0.6735	0.4671	1.4418	0.1516
age 25-29	-0.5671	1.1622	-0.4880	0.6263
age 30-39	-0.0449	1.8273	-0.0246	0.9804
age 40-49	1.0125	2.0939	0.4836	0.6295
age 50-59	-0.1267	2.6677	-0.0475	0.9622
gender Male	-0.4420	0.8667	-0.5100	0.6109
occupation group Employed Student	2.9556	1.8178	1.6259	0.1063
occupation group Student	2.3064	1.5265	1.5109	0.1331
GenAI Use 4-7h & AI Productive Use	-0.6851	1.3228	-0.5179	0.6054
GenAI Use 8-15h & AI Productive Use	-2.0414	1.5289	-1.3352	0.1840
GenAI Use Less than 1h & AI Productive Use	-0.3250	1.3184	-0.2465	0.8057
GenAI Use More than 15h & AI Productive Use	1.3464	1.6645	0.8089	0.4200
GenAI Use 4-7h & AI Emotional Use	-0.8766	0.9279	-0.9447	0.3465
GenAI Use 8-15h & AI Emotional Use	-0.3184	0.9348	-0.3406	0.7339
GenAI Use Less than 1h & AI Emotional Use	1.6026	1.9610	0.8173	0.4152
GenAI Use More than 15 & AI Emotional Use	4.0227	2.5516	1.5766	0.1172

8.6 Appendix F

Table 14. Multiple Linear Regression statistic for GenAI Use Patterns and Rumination.

r squared	adj r squared	f statistic	df1	df2	p value	n
0.4072	0.3427	6.3112	16	147	1.45E-10	164

Table 15. Multiple Linear Regression for GenAI use patterns and Rumination.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**25.3494**	**3.9771**	**6.3738**	**2.24E-09**
AI Productive Use	0.3856	0.4099	0.9407	0.3484
AI Casual Use	**1.4985**	**0.5697**	**2.6303**	**0.0094**
AI Emotional Use	0.8013	0.4553	1.7599	0.0805
GenAI Literacy	0.1876	0.7847	0.2391	0.8113
Extraversion	**-0.8182**	**0.2834**	**-2.8870**	**0.0045**
Agreeableness	-0.2800	0.3511	-0.7976	0.4264
Conscientiousness	-0.4074	0.3696	-1.1022	0.2722
Emotional Stability	**-1.4358**	**0.3130**	**-4.5869**	**9.56E-06**
Openness	0.6236	0.4347	1.4346	0.1535
gender Female	0.9968	0.8016	1.2436	0.2156
occupation group Employed Student	-0.0455	1.2288	-0.0370	0.9705
occupation group Employed	**-2.8313**	**1.4227**	**-1.9902**	**0.0484**
age 25-29	-0.6627	1.1104	-0.5968	0.5515
age 30-39	0.1100	1.6955	0.0649	0.9484
age 40-49	0.4737	1.9689	0.2406	0.8102
age 50-59	0.1865	2.4832	0.0751	0.9402

8.7 Appendix G

Table 16. Multiple Linear Regression statistic for GenAI Use, GenAI Use Patterns and Rumination.

r squared	adj r squared	f statistic	df1	df2	p value	n
0.4267	0.3465	5.3220	20	143	7.29E-10	164

Table 17. Multiple Linear Regression for GenAI Use, GenAI Use Patterns and Rumination.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**27.4687**	**4.1417**	**6.6323**	**6.32E-10**
GenAI Use 1-3h	-2.2281	1.2382	-1.7994	0.07406
GenAI Use 4-7h	-1.0261	1.3949	-0.7356	0.4632
GenAI Use 8-15h	-0.1721	1.5976	-0.1077	0.9144
GenAI Use More than 15h	-1.0414	2.0854	-0.4994	0.6183
AI Productive Use	0.4109	0.4658	0.8823	0.3791
AI Casual Use	**1.4875**	**0.5702**	**2.6090**	**0.0100**
AI Emotional Use	**0.9880**	**0.4684**	**2.1095**	**0.0366**
GenAI Literacy	0.0438	0.8108	0.0540	0.9570
age 25-29	-0.8061	1.1103	-0.7260	0.4690
age 30-39	0.1232	1.7128	0.0719	0.9428
age 40-49	0.9026	2.0014	0.4510	0.6527
age 50-59	-0.1513	2.4960	-0.0606	0.9518
gender Female	0.6108	0.8271	0.7385	0.4614
Extraversion	**-0.8953**	**0.2863**	**-3.1268**	**0.0021**
Agreeableness	-0.3558	0.3609	-0.9861	0.3258
Conscientiousness	-0.4028	0.3717	-1.0836	0.2804
Emotional Stability	**-1.4400**	**0.3128**	**-4.6037**	**9.08E-06**
Openness	0.6269	0.4356	1.4392	0.1523
occupation group Employed Student	0.0982	1.2416	0.0791	0.9371
occupation group Employed	**-3.0132**	**1.4263**	**-2.1125**	**0.0364**

8.8 Appendix H

Table 18. Linear Regression for AI Casual Use and Reflection statistics.

R^2	Adjusted R^2	F Statistic	DF1	DF2	P Value	N
0.3019	0.2207	3.7149	17	146	6.68E-06	164

Table 19. Linear Regression for AI Casual Use and Reflection.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**11.7042**	**2.5427**	**4.6031**	**8.97E-06**
AI Casual Use	**1.0877**	**0.2689**	**4.0447**	**8.45E-05**
GenAI Literacy Awareness	-0.4790	0.3444	-1.3908	0.1664
GenAI Literacy Usage	-0.4431	0.3805	-1.1644	0.2461
GenAI Literacy Evaluation	**1.2232**	**0.4511**	**2.7116**	**0.0075**
GenAI Literacy Ethics	-0.2950	0.3782	-0.7799	0.4367
Extraversion	**-0.3597**	**0.1797**	**-2.0023**	**0.0471**
Agreeableness	-0.2582	0.2160	-1.1951	0.2340
Conscientiousness	**-0.5454**	**0.2355**	**-2.3159**	**0.0220**
Emotional Stability	-0.2174	0.1949	-1.1153	0.2665
Openness	0.4898	0.2696	1.8163	0.0714
age 25-29	-0.1405	0.7089	-0.1982	0.8432
age 30-39	-0.3791	1.0476	-0.3618	0.7180
age 40-49	-0.8356	1.2311	-0.6788	0.4984
age 50-59	-0.4546	1.5575	-0.2919	0.7708
gender Male	-0.5889	0.5101	-1.1545	0.2502
occupation group Employed Student	0.5416	1.0470	0.5173	0.6057
occupation group Student	1.0813	0.8756	1.2349	0.2189

Table 20. Linear Regression for AI Emotional Use and Reflection statistics.

R^2	Adjusted R^2	F Statistic	DF1	DF2	P Value	N
0.353	0.278	4.683	17	146	8.07E-08	164

Table 21. Linear Regression for AI Emotional Use and Reflection.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**11.6686**	**2.3736**	**4.9160**	**2.35E-06**
AI Emotional Use	**1.1185**	**0.2072**	**5.3976**	**2.67E-07**
GenAI Literacy Awareness	-0.3397	0.3334	-1.0189	0.3100
GenAI Literacy Usage	-0.5426	0.3667	-1.4796	0.1411
GenAI Literacy Evaluation	**1.1554**	**0.4348**	**2.6575**	**0.0087**
GenAI Literacy Ethics	-0.4121	0.3634	-1.1341	0.2586
Extraversion	**-0.3527**	**0.1730**	**-2.0391**	**0.0432**
Agreeableness	-0.2748	0.2078	-1.3223	0.1881
Conscientiousness	**-0.5749**	**0.2237**	**-2.5695**	**0.0112**
Emotional Stability	-0.2394	0.1877	-1.2750	0.2043
Openness	**0.5288**	**0.2586**	**2.0448**	**0.0427**
age 25-29	-0.1360	0.6826	-0.1993	0.8423
age 30-39	0.0773	1.0070	0.0767	0.9389
age 40-49	0.0077	1.1888	0.0065	0.9948
age 50-59	0.1780	1.5071	0.1181	0.9061
gender Male	-0.3924	0.4939	-0.7945	0.4282
occupation group Employed Student	1.1608	1.0214	1.1365	0.2576
occupation group Student	1.1379	0.8413	1.3525	0.1783

Table 22. Linear Regression for AI Emotional Use and AI Casual Use and Reflection statistics.

R^2	Adjusted R^2	F Statistic	DF1	DF2	P Value	N
0.3568	0.2770	4.4690	18	145	1.26E-07	164

Table 23. Linear Regression for AI Emotional Use and AI Casual Use and Reflection.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**11.0773**	**2.4556**	**4.5111**	**1.32E-05**
AI Emotional Use	**0.9535**	**0.2711**	**3.5172**	**0.0006**
AI Casual Use	0.3200	0.3387	0.9447	0.3464
GenAI Literacy Awareness	-0.3497	0.3337	-1.0478	0.2965
GenAI Literacy Usage	-0.5257	0.3673	-1.4313	0.1545
GenAI Literacy Evaluation	**1.1470**	**0.4350**	**2.6366**	**0.0093**
GenAI Literacy Ethics	-0.3805	0.3651	-1.0422	0.2991
Extraversion	**-0.3492**	**0.1731**	**-2.0176**	**0.0455**
Agreeableness	-0.2862	0.2082	-1.3745	0.1714
Conscientiousness	**-0.5401**	**0.2268**	**-2.3810**	**0.0186**
Emotional Stability	-0.2438	0.1879	-1.2976	0.1965
Openness	**0.5571**	**0.2604**	**2.1393**	**0.0341**
age 25-29	-0.1429	0.6828	-0.2092	0.8346
age 30-39	-0.0312	1.0139	-0.0308	0.9755
age 40-49	-0.1543	1.2015	-0.1284	0.8980
age 50-59	0.1187	1.5090	0.0787	0.9374
gender Male	-0.4028	0.4942	-0.8151	0.4163
occupation group Employed Student	1.1310	1.0223	1.1064	0.2704
occupation group Student	1.1979	0.8440	1.4193	0.1580